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# Responses of vegetation to climatic variations in the desert region of northern China

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ABSTRACT

Global climate change is expected to impact vegetation dynamics. However, differences in the responses of vegetation in desert regions remain poorly understood. We analysed trends in normalised difference vegetation index (NDVI) and its correlations with climatic factors (temperature and precipitation) for typical vegetation in dry sub-humid, semi-arid, arid, and hyper-arid regions of northern China over the past three decades (1982–2015). We also evaluated the effects of climatic variations on vegetation using the vegetation sensitivity index (VSI). Over the study period, NDVI in the dry sub-humid and semi-arid regions showed a significant increasing trend, but no marked trend was noted in the arid region. Both precipitation and temperature had positive effects on NDVI, but that of the latter on NDVI decreased with increasing aridity. The VSI of vegetation dominated by *Pinus sylvestris* var. *mongolica*, *Ulmus* spp., and *Caragana* spp. was higher than that of vegetation dominated by *Artemisia desertorum*, *A. ordosica*, *Haloxylon persicum*, and *H. ammodendron*. Our analysis provides two important insights into the responses of vegetation to climatic variations: Firstly, vegetation in the different desert regions of northern China showed diverse responses to climatic variations. Secondly, vegetation dominated by trees (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) and tall shrubs (*Caragana* spp.) was more sensitive to climatic variations than that dominated by drought-tolerant dwarf shrubs (e.g. *A. desertorum* and *A. ordosica*).

## 1. Introduction

It is widely accepted that climate change is affecting global ecosystems. There is sufficient evidence indicating that the potential collapse of some ecosystems (e.g. the Amazon rainforest, boreal forests, and tundra) is related to climate change (Bonan, 2008; Hoorn et al., 2010; Myers-Smith et al., 2015). Due to water limitation, infertile soil, and sparse vegetation, desert ecosystems, may be particularly vulnerable to climate change (Kong et al., 2017; Seddon et al., 2016). It has been estimated that land degradation caused by desertification affects one-quarter of the world's land surface, containing one-fifth of the world's population, mostly living in developing countries (D'Odorico et al., 2013). This number will substantially increase in the coming decades, given the forecasted increased in aridity linked to climate change and the high population growth of most developing countries (Huang et al., 2015). Consequently, there are many uncertainties in and challenges to achieving the 'Zero Net Land Degradation' goal envisaged by the United Nations Convention to Combat Desertification (UNCCD, 2012). Precise knowledge of the influence of climate change on desert ecosystems is therefore urgent and integral to their protection (Vogt et al., 2011).

Vegetation, as an active component of ecosystems (including desert ecosystems), links the soil and atmosphere through energy and mass transport; thus, it is a sensitive indicator of environmental change (Piao et al., 2006). Monitoring vegetation dynamics and analysing their responses to climatic variations are popular approaches to studying global climate change (Virtanen et al., 2010; Svenning and Sandel, 2013; Yin et al., 2016). The responses of a wide variety of vegetation to climatic variations across different regions have been researched and identified (Craine et al., 2012; Clinton et al., 2014). For example, in the North American prairie, responses of grasslands climate change vary because different species respond differently to climate change, and shallow-rooted, short-lived grasses may be especially sensitive to climatic variations.

Among climatic factors, mean annual precipitation is the main limiting factor of vegetation activity (Craine et al., 2012; Seddon et al.,

*Abbreviations:* AI, aridity index; NDVI, normalised difference vegetation index; VSI, vegetation sensitivity index

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2016). In the Amazon rainforest, prolonged tropical droughts can selectively kill trees and may alter species composition; fast-growing, light-wooded trees may be especially vulnerable to drought. Simultaneously, dry conditions may cause parts of the Amazon to green up. This boost in tropical productivity may be due to increased solar radiation (Clinton et al., 2014; Holmgren et al., 2013). Desert regions have high spatial heterogeneity, with known relationships between vegetation and climatic factors. For example, in the Inner Mongolia grasslands, changes in vegetation are consistent with shifts in both temperature and precipitation, implying that vegetation growth is more sensitive to the combined effect of water and heat, rather than that of either single climatic factor (Mu et al., 2013; Li et al., 2015). In the desert steppe of Xinjiang, northwest China, vegetation has generally shown a greening trend in recent decades, and precipitation has been identified as the main factor driving this process (Shi et al., 2007; Zhou et al., 2014). However, knowledge of the responses of different types of vegetation to climatic variations is relatively poor.

In China, deserts and desertification land cover over 2.4 million $km^2$ (Chen and Tang, 2005), accounting for more than a quarter of the land area, from the Hulun Buir (dry sub-humid region) to Taklimakan (hyper-arid region). Desertification is related to a range of issues, such as declining productivity, biodiversity loss, land degradation, and deteriorating ecosystem services. It has therefore become one of the most serious ecological and social problems in China (T. Wang et al., 2015; X. Wang et al., 2015; Yang et al., 2005). However, desertification has been suppressed in some regions through ecological engineering such as the Three-North Shelter Forest Program (Fu et al., 2011). Moreover, in past decades, frequent climatic variations have profoundly affected the structure and function of regional ecosystems, leading to uncertainties regarding ecological restoration in desert regions (Zhou et al., 2015). Given these climatic variations, studying vegetation dynamics and its relationship with climatic factors is important for understanding how the changing climate is altering desert ecosystems (Wang et al., 2013).

In this study, we selected the area dominated by nine representative vegetation types (*Pinus sylvestris* var. *mongolica*, *Ulmus* spp., *Caragana* spp., *Artemisia desertorum*, *A. ordosica*, *Salsola passerina*, *Reaumuria songarica*, *Haloxylon persicum*, and *H. ammodendron*, respectively) in the desert region of northern China as the study area, to investigate their responses to climatic variations. We analysed a time series of meteorological datasets (temperature and precipitation) and the normalised difference vegetation index (NDVI) during 1982–2015 to examine trends and relationships, and evaluated the effects of climatic variations on vegetation using the vegetation sensitivity index (VSI). We had two specific aims: (1) to clarify differences in responses of vegetation in desert regions to climatic variations; and (2) to identify relatively sensitive vegetation in the study area.

## 2. Methods

### 2.1. Study area

The desert region of northern China spans from 35 to 50°N to 75–125°E and covers over 2.4 million $km^2$ (Fig. 1). The annual precipitation and average temperature in this region were 50–372 mm and 4–12 °C during 1982 to 2015, respectively. According to the dryland classification by Middleton and Thomas (1997), the study area covered by nine vegetation types can be classified into four climatic regions (Fig. 1): dry sub-humid ($0.5 < AI < 0.65$), semi-arid ($0.2 < AI < 0.5$), arid ($0.05 < AI < 0.2$), and hyper-arid ($AI < 0.05$), where AI, aridity index, is the ratio between the mean annual precipitation and mean annual potential evaporation. The ecosystems of this region are mainly steppe, desert steppe, and desert (Zhang et al., 2018). The dominant species include coniferous trees (e.g. *P. sylvestris* var. *mongolica*), deciduous trees (e.g. *Ulmus* spp.), semi-dwarf arbours (e.g. *H. persicum* and *H. ammodendron*), tall shrubs (e.g. *Caragana* spp.), and dwarf shrubs (e.g. *A. desertorum*, *A. ordosica*, *S. passerina*, and *R. songarica*). More information on these species is given in Table 1.

### 2.2. Datasets

The meteorological data were collected from the China Meteorological Data Service Center (http://data.cma.cn/) via permanent meteorological stations across China; 187 long-term observation stations (35, 57, 43 and 20 stations in the dry sub-humid, semi-arid, arid, and hyper-arid regions, and 32 stations in the region with an $AI > 0.65$) with monthly air temperature and precipitation records from 1982 to 2015 were selected. We interpolated the meteorological data by thin-plate smoothing splines, following the method described by Hijmans et al. (2005), using ANUSPLIN version 4.3 software to obtain monthly raster data layers.

NDVI, with daily resolution from 1982 to 2015, was derived from the Land Long Term Data Record version 4 dataset to monitor long-term vegetation activity (https://ltdr.nascom.nasa.gov/). Maximum value composite technique was applied to obtain monthly time-series vegetation growth dynamics (Vermote and Saleous, 2006). Pixels with a mean growing season NDVI of < 0.05 were excluded to reduce the influence of sparsely vegetated pixels in this study (Zhang, 2015).

Vegetation with different dominant species was selected based on the vegetation map with a scale of 1:1,000,000 (the equivalent of approximately 250 × 250 m of the spatial resolution under 96 dpi). This map was provided by the Environmental and Ecological Science Data Center for West China (http://westdc.westgis.ac.cn/). The AI data included the 30-year average from 1981 to 2010, provided by the China National Climate Center and computed with potential evapotranspiration data following the United Nations Food and Agriculture Organization's Penman-Monteith method (Allen et al., 1998). All images were processed using Python 2.7, ArcGIS version 10.2, and the HDF-EOS to GeoTIFF Conversion Tool.

### 2.3. Analysis of trends and correlations

An ordinary least squares regression was performed to detect trends in NDVI and climatic factors (temperature and precipitation) in the growing season (April to October) during 1982–2015. The Pearson correlation coefficients ($r$) between the NDVI and climatic factors in the growing seasons during 1982–2015 were subsequently calculated for pixels (Piao, 2003). In addition, the pixel percentages were calculated to show positive or negative correlations between NDVI and climatic factors. Trends or correlations were classified into three ranks based on significance: prominently significant, $p < 0.01$; significant, $p < 0.05$; and not significant, $p > 0.05$. In this study, P and N stand for $r > 0$ and $r < 0$, respectively; P-sig for $r > 0$ and $p < 0.05$; and N-sig for $r < 0$ and $p < 0.05$.

### 2.4. Evaluation of vegetation sensitivity to climatic variations

VSI was first explored by Seddon et al. (2016) to assess the relative sensitivity of terrestrial ecosystems to climatic variations. Temperature and precipitation are the main climatic factors affecting vegetation activities in desert ecosystems (Seddon et al., 2016; Li et al., 2015; Yang et al., 2015); thus, they were used as the climate variables in the VSI equation:

$$VSI = \sum (TEM_{wei} \times TEM_{sen} + PRE_{wei} \times PRE_{sen}) \quad (1)$$

where $VSI$ is vegetation sensitivity, $TEM_{wei}$ and $PRE_{wei}$ are the relative importance of temperature and precipitation on vegetation change (climate weights), respectively, and $TEM_{sen}$ and $PRE_{sen}$ are the sensitivity of NDVI to temperature and precipitation, respectively. The VSI flow chart is shown in Fig. 2.

Firstly, a multiple regression approach was used to test linear relationships between NDVI and climatic factors:

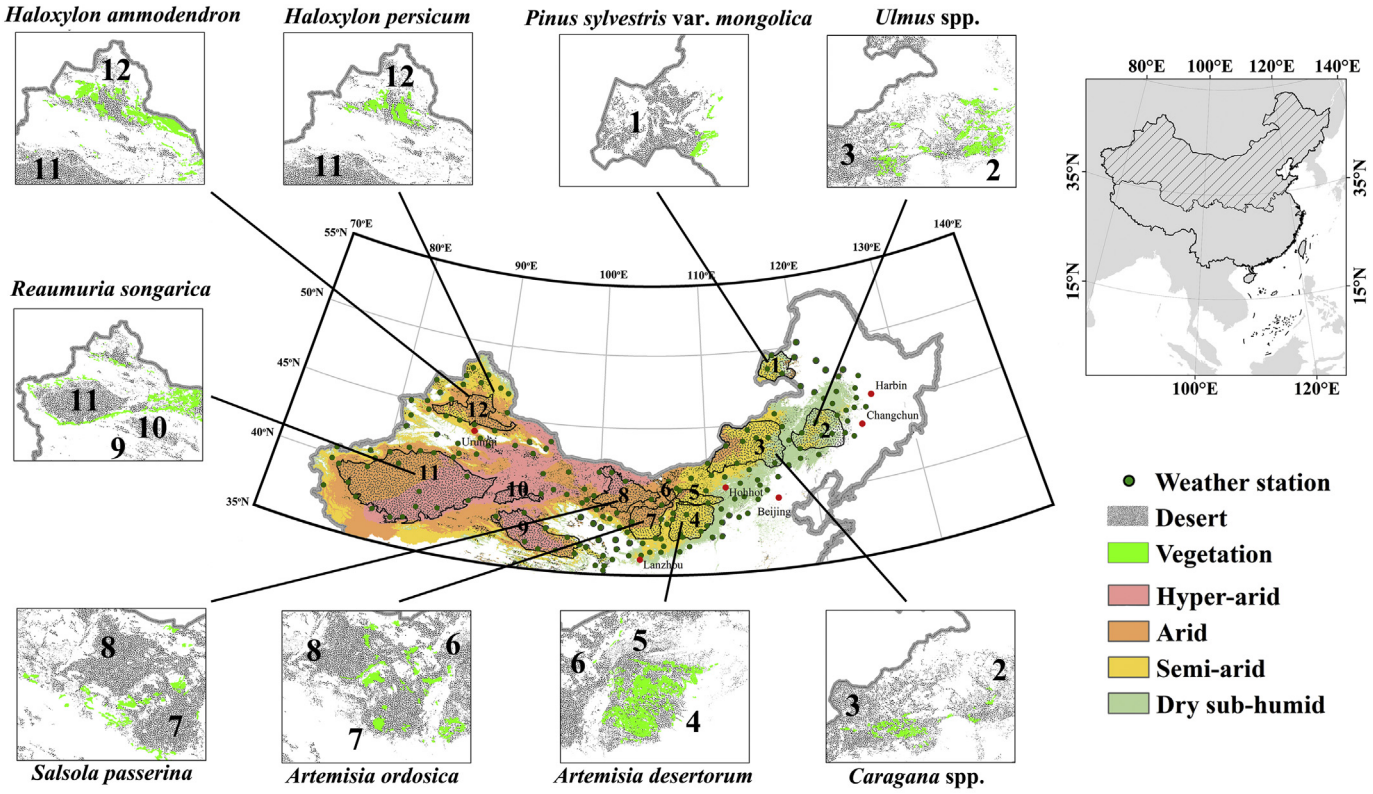


**Fig. 1.** Distribution of the vegetation selected in the desert region of northern China.

**Table 1**
Characteristics of representative vegetation dominated by nine species.

| Dominant species | Plant type | Plant height | Habitat precipitation (mm)[a] | Habitat temperature (°C)[a] | Area ($10^4$ km$^2$) | Desert | Climate type |
|---|---|---|---|---|---|---|---|
| *Pinus sylvestris* var. *mongolica* | Coniferous tree | ≤25 m | 400–600 | −1–1 | 0.26 | Hulun Buir | Dry sub-humid |
| *Ulmus* spp. | Deciduous tree | ≤25 m | 350–450 | 2.5–6.5 | 2.27 | Horqin Otindag | Dry sub-humid Semi-arid |
| *Caragana* spp. | Tall shrub | 0.7–2 m | 250–350 | 2.5–7 | 0.98 | Otindag | Semi-arid |
| *Artemisia desertorum* | Dwarf shrub | ≤70 cm | 250–400 | 5–9 | 3.48 | Mu Us Hobq | Semi-arid |
| *Artemisia ordosica* | Dwarf shrub | 50–70 cm | 80–300 | 7–9.5 | 1.51 | Tengger Badan Jaran | Semi-arid Arid |
| *Salsola passerina* | Dwarf shrub | 15–30 cm | 50–150 | 5–9 | 1.15 | Tengger Badan Jaran | Semi-arid Arid |
| *Reaumuria songarica* | Dwarf shrub | 10–30 cm | 30–200 | 5–10 | 17.34 | Kumtag Taklimakan | Semi-arid Arid Hyper-arid |
| *Haloxylon persicum* | Semi-dwarf arbour | ≤7 m | 150–250 | 4.5–8 | 2.67 | Gurbantunggut | Arid |
| *Haloxylon ammodendron* | Semi-dwarf arbour | 1–9 m | 30–250 | 6–10 | 4.52 | Gurbantunggut | Arid Hyper-arid |

[a] Habitat precipitation/temperature represents the mean annual precipitation/temperature in the habitat of the corresponding species.

$$NDVI = a \times PRE + b \times TEM + c \times NDVI_{t-1} + \varepsilon \quad (2)$$

where *PRE* and *TEM* represent precipitation and temperature, respectively,$NDVI_{t-1}$ is one-month-lagged NDVI monthly data to investigate the potential influence of memory effects, and $\varepsilon$ denotes the residual of this regression equation.

To estimate the relative importance of the three variables driving monthly changes in NDVI, all time-series data were transformed to z-score anomalies using monthly means and standard deviations. To remove any effects of collinearity among the three predictor variables, principal components regression (PCR) was used to identify the relative importance of each variable in driving monthly variations of NDVI in each pixel. The principal components that had significant relationships with climate ($p < 0.1$) were selected, and we subsequently multiplied the loading scores of each variable by the PCR coefficients. The product scores were summed to estimate the relative importance of each variable in driving monthly changes in NDVI, which provided an empirical

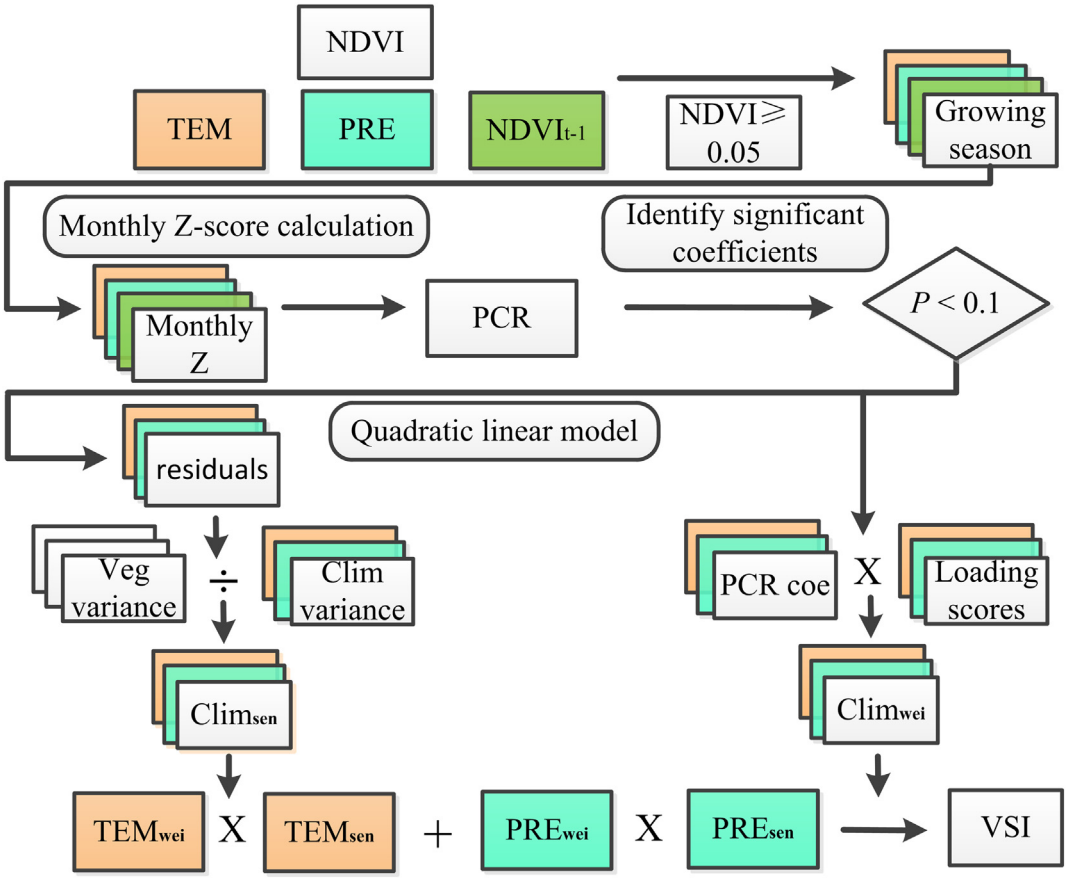


**Fig. 2.** Flow chart of the algorithm used to estimate the vegetation sensitivity index. PRE and TEM represent precipitation and temperature, respectively; $NDVI_{t-1}$ is one-month-lagged normalised difference vegetation index (NDVI), PCR stands for principal components regression, $TEM_{sen}$ and $PRE_{sen}$ are the sensitivity of NDVI to temperature and precipitation, respectively, and $TEM_{wei}$ and $PRE_{wei}$ refer to their weight, respectively.

approach for mapping the relative importance of climate on vegetation change (climate weights).

The climate weights from each variable were rescaled between 0 and 1 (using the minimum and maximum values of any of the climate coefficient values), to be used for calculations of vegetation sensitivity. To estimate the variations of both the climate variables and NDVI on these time series, we used the residuals of a quadratic linear model fitted to the mean-variance relationship of both the NDVI and climate variables for each pixel. We standardised the residuals (0–100) for each variable to unify calculation. Sensitivity metrics are the ratios between NDVI variability and each of the climate variables:

$$TEM_{sen} = \frac{NDVI_{var}}{TEM_{var}} \quad (3)$$

$$PRE_{sen} = \frac{NDVI_{var}}{PRE_{var}} \quad (4)$$

where $TEM_{sen}$ and $PRE_{sen}$ are the sensitivity of NDVI to temperature and precipitation, respectively, and $NDVI_{var}$, $TEM_{var}$, and $PRE_{var}$ represent the residuals of a quadratic linear model fitted to the mean-variance relationship of NDVI, temperature, and precipitation, respectively. Each ratio was weighted according to the importance of the climate variable to NDVI variability by multiplying it by the value of the regression coefficient (climate weights). Finally, the VSI is the sum of the sensitivity scores for each variable, as shown in Eq. (1). To display it directly on the map, VSI was rescaled between 0 and 100. The larger the VSI is, the more sensitive the vegetation is to climatic variations. All data analyses were computed using the *R* project.

## 3. Results

### 3.1. Variations in climatic factors during growing seasons

In general, most of the study area (60.1%) displayed a significant warming trend ($p < 0.05$) over the past 34 years; 23.6% of the study area showed a warming trend, but did not pass the significance test (Fig. 3a). There were no regions where the temperature had a significantly decreasing trend during the growing seasons. Moreover, of the four climatic regions, almost all showed a significantly increasing trend in temperature (Table 2). The dry sub-humid region dominated by *P. sylvestris* var. *mongolica* had the strongest increasing trend ($0.044\ ^{\circ}C\ yr^{-1}$, $R^2 = 0.67$, $p = 0.008$), which corresponds to a net warming of 1.50 °C over the entire study period. In the semi-arid region, the increasing rate was approximately $0.030\ ^{\circ}C\ yr^{-1}$ (1.02 °C of net warming over the study period), which was lower than that in the dry sub-humid region. The arid and hyper-arid regions, areas with a relatively strong increasing trend in temperature ($> 0.04\ ^{\circ}C\ yr^{-1}$, > 1.36 °C of net warming over 34 years), were dominated by *H. ammodendron* and *H. persicum*, whereas areas with a relatively weak increasing trend ($< 0.04\ ^{\circ}C\ yr^{-1}$, < 1.36 °C of net warming over 34 years) were dominated by *R. songarica* and *A. ordosica*.

Over the past 34 years, only a small proportion of the study area (approximately 14.1%) showed a significantly increasing trend ($p < 0.05$) in precipitation; 62.4% of the study area showed an increasing trend but did not pass the significance test (Fig. 3b). Specifically, in the dry sub-humid region, precipitation during the growing season presented a decreasing trend, and the areas dominated by *Ulmus* spp. showed the strongest decreasing trend ($1.18\ mm\ yr^{-1}$, $R^2 = 0.34$,

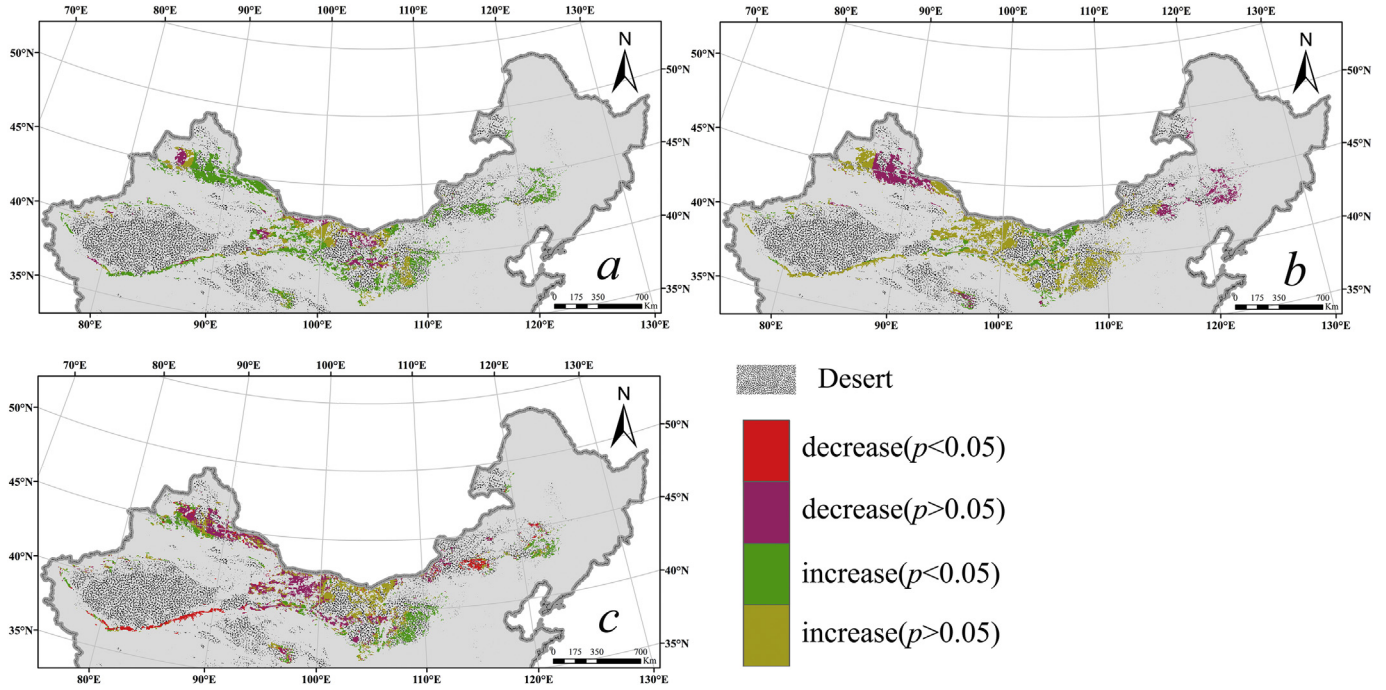


**Fig. 3.** Spatial distributions of interannual trends in normalised difference vegetation index (NDVI) and climatic factors over desert regions during growing seasons (1982–2015): a) interannual trend in growing season temperature, b) interannual trend in growing season precipitation, and c) interannual trend in growing season NDVI.

$p = 0.62$), which corresponds to a net decrease of 40.12 mm over the entire period. In the semi-arid and arid regions, the increasing trend ($> 0.4$ mm yr$^{-1}$, $> 13.6$ mm net increase over 34 years) appeared in areas dominated by *A. ordosica* and *S. passerine*, whereas the opposite trend was detected in areas dominated by *R. songarica*. Precipitation presented an increasing trend ($p > 0.05$) in the hyper-arid region.

### 3.2. Variations in NDVI during growing seasons

Just over half of the study area (56.3%) showed an increasing trend in NDVI, 16.8% presented a significant increasing trend ($p < 0.05$), and only 5.5% showed a significant decreasing trend (Fig. 3c). NDVI in five localities showed a significant interannual trend ($p < 0.05$), where NDVI either significantly increased (Horqin, Mu Us, and Gurbantunggut) or significantly decreased (Otindag and Taklimakan) over the study period. In terms of climatic region, in the dry sub-humid and semi-arid regions, NDVI generally showed a significant increasing trend ($p < 0.01$), and the vegetation dominated by *A. desertorum* showed the strongest increasing trend ($1.92 \times 10^{-3}$ yr$^{-1}$, $R^2 = 0.76$, $p = 0.005$). In the arid and hyper-arid regions, NDVI generally showed increasing trends ($p > 0.05$). However, only the NDVI of vegetation dominated by *H. persicum* showed a significant decreasing trend ($0.43 \times 10^{-3}$ yr$^{-1}$, $R^2 = 0.54$, $p = 0.006$). In general, trends in NDVI in the arid and hyper-arid regions were less notable compared with those in the dry sub-humid and semi-arid regions.

### 3.3. Correlations between NDVI and climatic factors

The pixel percentages of NDVI that positively correlated with temperature were varied across the four climatic regions (Table 3). In the dry sub-humid region, > 80% of the study area was positively correlated with temperature. In the semi-arid and arid regions, it was approximately 70, and > 60%, respectively. In the hyper-arid region, for vegetation dominated by *R. songarica* and *H. ammodendron*, 44.2% and

**Table 2**
Interannual trends in climatic factors and normalised difference vegetation index (NDVI) during the growing seasons of 1982–2015.

| Climate type | Dominant species | TEM (°C yr$^{-1}$) | PRE (mm yr$^{-1}$) | NDVI ($10^{-3}$ yr$^{-1}$) |
|---|---|---|---|---|
| Dry sub-humid | *Pinus sylvestris* | 0.044** | −0.19 | 1.76** |
| | *Ulmus* spp. | 0.036** | −1.24 | 1.14* |
| Semi-arid | *Ulmus* spp. | 0.030** | −1.18 | 0.35 |
| | *Caragana* spp. | 0.041** | −0.13 | 0.18 |
| | *Artemisia desertorum* | 0.029** | 0.41 | 1.92** |
| | *Artemisia ordosica* | 0.036** | 0.49 | 0.72** |
| | *Salsola passerine* | 0.038** | 0.56 | 1.38** |
| | *Reaumuria songarica* | 0.032** | 0.79 | 1.08** |
| Arid | *Reaumuria songarica* | 0.022* | −0.13 | 0.54 |
| | *Artemisia ordosica* | 0.002 | 1.13 | 0.00 |
| | *Haloxylon persicum* | 0.042** | −0.14 | 0.84** |
| | *Haloxylon ammodendron* | 0.037** | 0.21 | 0.38 |
| | *Salsola passerine* | 0.033** | 0.64 | 0.27 |
| Hyper-arid | *Reaumuria songarica* | 0.016* | 0.51 | −0.43** |
| | *Haloxylon ammodendron* | 0.043** | 0.34 | 0.00 |

* Statistical significance of linear regression of Pearson correlation ($p < 0.05$).
** Statistical significance of linear regression of Pearson correlation ($p < 0.01$).

**Table 3**
Pixel percentage of the correlations between normalised difference vegetation index (NDVI) and temperature (P and N stand for $r > 0$ and $r < 0$, respectively, P-sig for $r > 0$ and $p < 0.05$, and N-sig for $r < 0$ and $p < 0.05$).

| Climate type | Dominant species | Growing seasons | | | |
|---|---|---|---|---|---|
| | | P | P-sig | N | N-sig |
| Dry sub-humid | *Pinus sylvestris* | 19.0 | 72.4 | 4.7 | 3.9 |
| | *Ulmus* spp. | 49.3 | 31.1 | 18.0 | 1.6 |
| Semi-arid | *Ulmus* spp. | 48.2 | 14.5 | 29.9 | 7.4 |
| | *Caragana* spp. | 54.4 | 4.2 | 40.0 | 1.4 |
| | *Artemisia desertorum* | 71.2 | 14.7 | 13.9 | 0.2 |
| | *Artemisia ordosica* | 51.2 | 8.6 | 39.1 | 1.1 |
| | *Salsola passerine* | 66.9 | 14.3 | 18.7 | 0.1 |
| | *Reaumuria songarica* | 43.2 | 15.9 | 39.0 | 2.9 |
| Arid | *Reaumuria songarica* | 50.6 | 8.3 | 39.1 | 2.0 |
| | *Artemisia ordosica* | 64.4 | 0.2 | 35.3 | 0.1 |
| | *Haloxylon persicum* | 61.8 | 2.5 | 34.6 | 1.1 |
| | *Haloxylon ammodendron* | 63.5 | 2.5 | 29.7 | 4.9 |
| | *Salsola passerine* | 50.6 | 10.3 | 37.9 | 1.2 |
| Hyper-arid | *Reaumuria songarica* | 43.0 | 1.2 | 52.9 | 2.9 |
| | *Haloxylon ammodendron* | 48.9 | 1.1 | 48.9 | 1.1 |

50.0% of the pixels, respectively, were positively correlated with temperature. Those negatively correlated with temperature were 45.8 and 50.0%, respectively.

Precipitation exerted positive effects on NDVI in the dry sub-humid and hyper-arid regions (Table 4). The pixel percentage of NDVI positively correlated with precipitation was over 60%, and as high as 86.4% for vegetation dominated by *A. desertorum* in the semi-arid region (Table 4). In the arid region, for vegetation dominated by *H. persicum* and *H. ammodendron*, the pixel percentages of positive correlation between NDVI and precipitation were approximately 60%, lower than for other vegetation (> 70%) in the same climatic region.

### 3.4. Vegetation sensitivity to climatic variations

The distribution of VSI represented prominent spatial differences (Fig. 4). The higher VSIs emerged predominantly in the east (e.g. Horqin and Otindag), and the lower VSIs were mainly detected in the Mu Us and Gurbantunggut. In other words, vegetation dominated by *P. sylvestris* var. *mongolica*, *Ulmus* spp., *Caragana* spp., and *S. passerina* were more sensitive to climatic variations than that dominated by *A. desertorum*, *A. ordosica*, *H. persicum*, and *H. ammodendron*. Among all vegetation examined, that dominated by *A. desertorum* presented the lowest VSI (Table 5). Notably, the same vegetation in different climatic regions showed distinct VSIs (e.g. *Ulmus* spp. and *A. ordosica*; Table 5).

**Table 4**
Pixel percentages of the correlations between normalised difference vegetation index (NDVI) and precipitation (P and N stand for $r > 0$ and $r < 0$, respectively, P-sig for $r > 0$ and $p < 0.05$, and N-sig for $r < 0$ and $p < 0.05$).

| Climate type | Dominant species | Growing seasons | | | |
|---|---|---|---|---|---|
| | | P | P-sig | N | N-sig |
| Dry sub-humid | *Pinus sylvestris* | 64.7 | 11.4 | 22.8 | 1.1 |
| | *Ulmus* spp. | 53.4 | 25.7 | 20.6 | 0.3 |
| Semi-arid | *Ulmus* spp. | 37.6 | 47.4 | 14.9 | 0.1 |
| | *Caragana* spp. | 54.8 | 22.3 | 22.7 | 0.2 |
| | *Artemisia desertorum* | 73.7 | 12.7 | 13.5 | 0.1 |
| | *Artemisia ordosica* | 67.6 | 2.4 | 29.9 | 0.1 |
| | *Salsola passerine* | 67.6 | 5.0 | 27.3 | 0.1 |
| | *Reaumuria songarica* | 53.8 | 24.1 | 21.2 | 0.9 |
| Arid | *Reaumuria songarica* | 68.4 | 0.8 | 30.6 | 0.2 |
| | *Artemisia ordosica* | 60.6 | 6.7 | 31.8 | 0.9 |
| | *Haloxylon persicum* | 52.7 | 6.8 | 40.0 | 0.5 |
| | *Haloxylon ammodendron* | 54.1 | 9.3 | 36.0 | 0.6 |
| | *Salsola passerine* | 87.6 | 10.5 | 1.8 | 0.1 |
| Hyper-arid | *Reaumuria songarica* | 60.2 | 0.9 | 38.1 | 0.8 |
| | *Haloxylon ammodendron* | 59.8 | 1.5 | 38.6 | 0.1 |

Overall, in 62.8% of the study area, temperature contributed < 50% to VSI (Fig. 5a), and it was mainly in the Gurbantunggut where temperature contributed > 50% to VSI. In contrast, in 62.8% of the study area, precipitation contributed > 50% (Fig. 5b), and in the Gurbantunggut, precipitation contributed < 50% to VSI. In terms of climatic regions, in dry sub-humid and semi-arid regions, precipitation contributed about 55% to VSI (Table 5). In arid and hyper-arid regions, precipitation contributed the most to the VSI of vegetation dominated by *S. passerina* (67.7%), and temperature contributed > 50% to vegetation dominated by *H. persicum* and *H. ammodendron* (61.0 and 56.0%, respectively).

## 4. Discussion

### 4.1. Differences in responses of vegetation to climatic variations

Our results show that the warming climate over the study period had varying effects on the NDVI of vegetation in the study area. Specifically, in the dry sub-humid region (e.g. Hulun Buir) and semi-arid region (e.g. Horqin), NDVI presented increasing trends ($p < 0.05$). However, there was no obvious trend in the arid region (e.g. Tengger), and decreasing NDVI was found in the hyper-arid region (e.g. Taklimakan) (Table 2). Because we only analysed areas covered by the nine vegetation types, other areas may have different trends and magnitudes, such as Taklimakan, where some areas have shown a greening trend over time (Zhao et al., 2011). Many studies have suggested that the warming climate is the one of main driving factors of greening in northern China (Forzieri et al., 2018; Li et al., 2015; Piao et al., 2015), because such a warming trend can enhance photosynthesis and increase vegetation activity (Sun et al., 2015). However, in this study, we found that the positive effects of temperature on NDVI decreased with degree of aridity. In the dry sub-humid region, the pixel percentages of NDVI that were positively correlated with temperature were > 80%. In the semi-arid region, it was approximately 70%, and in the hyper-arid region, it was only about 50% (Table 3).

Warming across northern China is indisputable, but the magnitude of warming in different sub-regions remains controversial. The peak changes of 1–1.5 °C over the study period (1981–2015) reflect the previous records, such as 1.2 °C in northern China (Piao et al., 2010) and 2 °C in the Mu Us Desert (Xu et al., 2018). These deviations may be caused by incompletely overlapping years and seasons, different data sources, and varying analysis methods. Furthermore, in the hyper-arid region, we detected that NDVI of vegetation dominated by *R. songarica* had a significant decreasing trend over the past 34 years (Table 2). These results suggest that the responses of vegetation to temperature varied across the different climatic regions of northern China. Under predicted future climate change, temperatures will rise in the study area (Huang et al., 2015), which could increase evapotranspiration (Piao et al., 2010; Zeng et al., 2017), and may have negative impacts on vegetation in this arid environment. This implies that, if future precipitation does not increase, the existing vegetation in this area will be faced with drought, and management measures and policies for protecting vegetation resources should be improved.

Our results indicate that most of the study area showed an unremarkable increasing trend over time, similar to those found by another study in the Mu Us Desert (Xu et al., 2018). However, both increasing (Piao et al., 2010) and decreasing trends (Xu et al., 2017) were detected in the study area in previous studies, potentially due to incompletely overlapping study periods. Thus, the precipitation trend of the whole desert region of northern China remains controversial. Our results showed that precipitation always had a positive effect on NDVI in the study area (Table 4). Increasing precipitation is the main driving force for enhancing vegetation activities in many ecosystems (Zhou et al., 2014). However, we did not explore the impacts of shifting

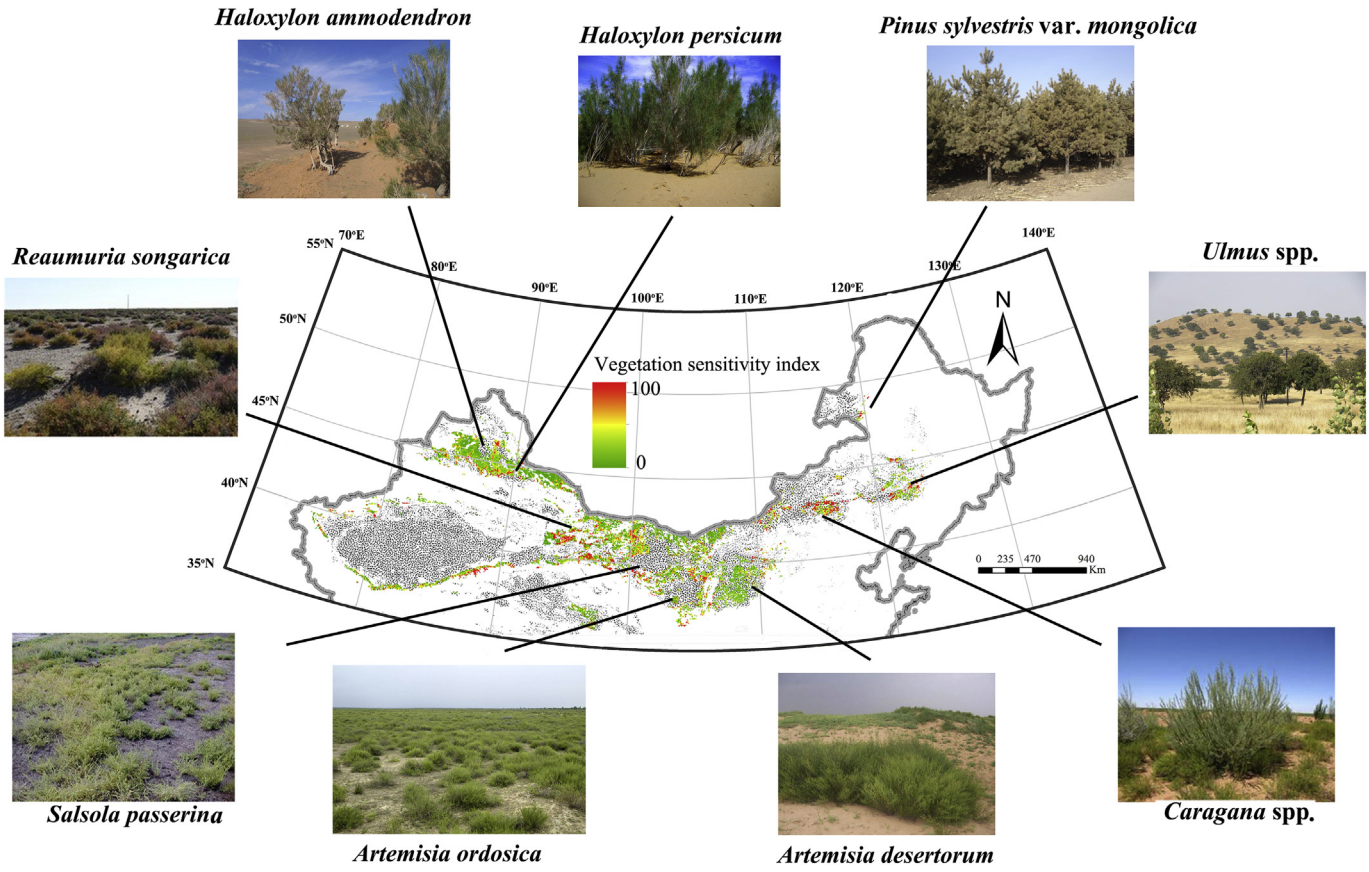


**Fig. 4.** Spatial distributions of vegetation sensitivity index.

**Table 5**
Vegetation sensitivity index and climatic factor contributions.

| Climate type | Dominant species | VSI | TEM (%) | PRE (%) |
|---|---|---|---|---|
| Dry sub-humid | *Pinus sylvestris* | 43.4 | 48.0 | 52.0 |
| | *Ulmus* spp. | 46.4 | 40.4 | 59.6 |
| Semi-arid | *Ulmus* spp. | 52.0 | 45.4 | 54.6 |
| | *Caragana* spp. | 47.1 | 43.0 | 57.0 |
| | *Artemisia desertorum* | 24.5 | 45.7 | 54.3 |
| | *Artemisia ordosica* | 26.5 | 45.5 | 54.5 |
| | *Salsola passerine* | 42.2 | 45.0 | 55.0 |
| | *Reaumuria songarica* | 35.4 | 43.4 | 56.6 |
| Arid | *Reaumuria songarica* | 29.3 | 38.3 | 61.7 |
| | *Artemisia ordosica* | 29.1 | 44.8 | 55.2 |
| | *Haloxylon persicum* | 28.8 | 61.0 | 39.0 |
| | *Haloxylon ammodendron* | 27.5 | 56.0 | 44.0 |
| | *Salsola passerine* | 45.7 | 32.3 | 67.7 |
| Hyper-arid | *Reaumuria songarica* | 28.7 | 37.4 | 62.6 |
| | *Haloxylon ammodendron* | 34.7 | 38.8 | 61.2 |

precipitation patterns on vegetation activities. Nevertheless, we found that the vegetation was more sensitive to variations in precipitation than to those in temperature, which implies that precipitation had a greater effect on vegetation variation. In fact, precipitation is one of the main drivers of short-term vegetation variation in the study area, especially during the early growing season (Zhang et al., 2018). In addition, low precipitation was usually accompanied by high temperatures, such as during spring drought. It is unanimously acknowledged that drought, the most widespread extreme climatic condition, profoundly affects the structure and function of ecosystems (Ratzmann et al., 2016). However, the direct effect of drought on vegetation was not explored in this study, and further research is therefore necessary.

### 4.2. Vegetation sensitivity

Our results show that the VSI of vegetation dominated by *P. sylvestris* var. *mongolica*, *Ulmus* spp., and *Caragana* spp. was higher than that dominated by *A. desertorum*, *A. ordosica*, *S. passerina*, and *R. songarica* (Table 5). This suggests that in terms of VSI, vegetation dominated by trees (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) and tall shrubs (*Caragana* spp.) was relatively more sensitive to climatic variations than dwarf-shrub vegetation was (*A. desertorum*, *A. ordosica*, *S. passerina*, and *R. songarica*). Other studies have also documented that temperature-induced drought stress limits tree activity more than that of shrubs (Barber et al., 2000), and compared with dwarf shrubs, tall shrubs are more sensitive to climate change (Young et al., 2016).

*Pinus sylvestris* var. *mongolica* and *Ulmus* spp. are viewed as excellent tree species for the reversal of desertification processes (Zhao et al., 2009) and have been widely promoted in eastern China deserts (Hulun Buir, Horqin, and Otindag). Moreover, *P. sylvestris* var. *mongolica*, as a rare evergreen tree species in desert regions, has been widely introduced across northern China (T. Wang et al., 2015; X. Wang et al., 2015). However, studies have indicated that vegetation dominated by *P. sylvestris* var. *mongolica* and *Ulmus* spp. have been degraded in recent years (Kang et al., 2004; T. Wang et al., 2015; X. Wang et al., 2015). In the Hulun Buir, large areas of *P. sylvestris* var. *mongolica* were browned due to declining soil moisture content (Kang et al., 2004; Liu et al., 2017). In the Otindag, the population structure of *Ulmus* spp. savanna has changed, and seedlings often suffer from severe water stress (Zhao et al., 2009; T. Wang et al., 2015; X. Wang et al., 2015). Our results show that the VSI of vegetation dominated by *P. sylvestris* var. *mongolica* and *Ulmus* spp. was relatively high over the study period (Table 5), implying that they are vulnerable to climatic variations.

Moreover, vegetation dominated by *Ulmus* spp. in the semi-arid region was more sensitive than that in the dry sub-humid region

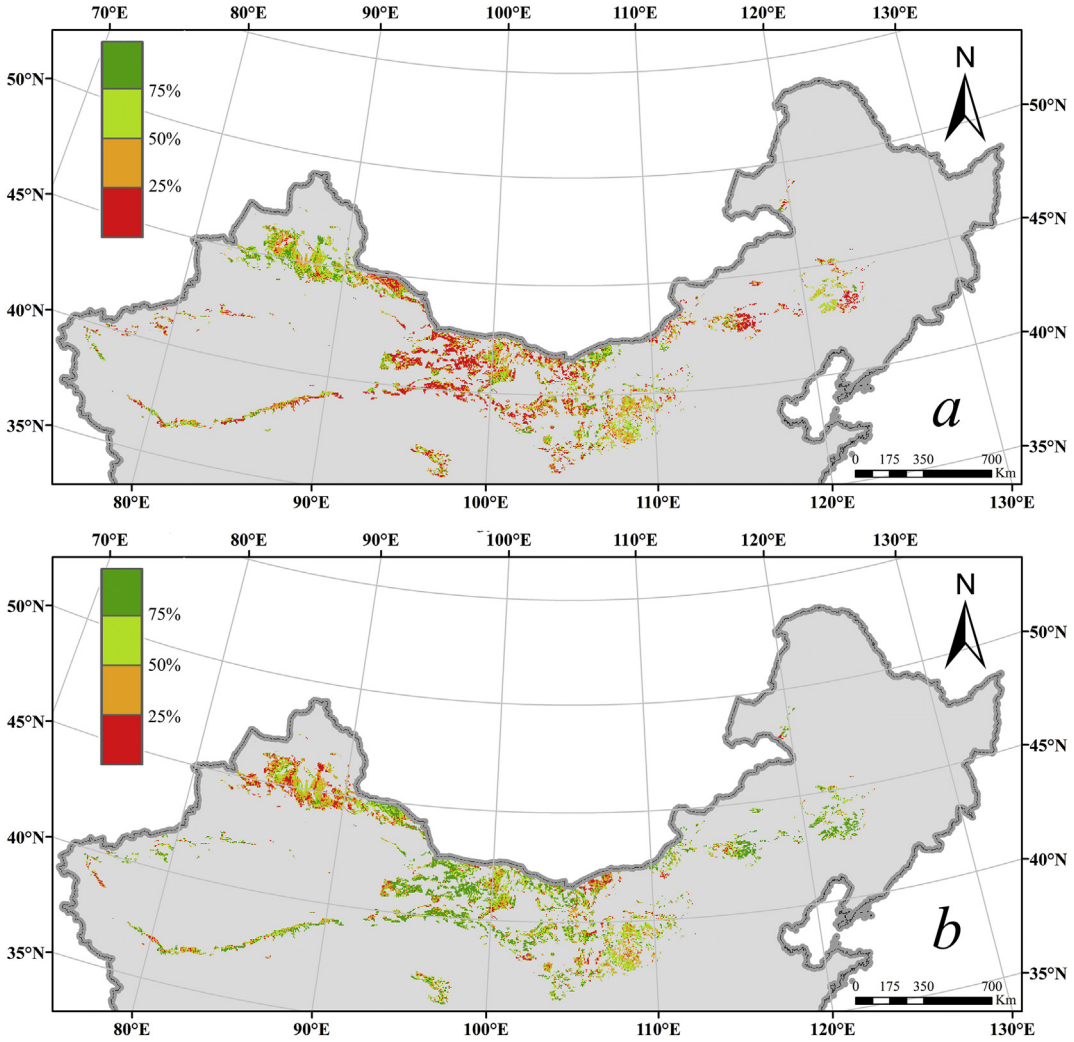


**Fig. 5.** Spatial distributions of climatic factor contributions to vegetation sensitivity index: a) temperature contributions to vegetation sensitivity index, b) precipitation contributions to vegetation sensitivity index.

(Table 5). Although we did not compare the VSI of *P. sylvestris* var. *mongolica* across different regions due to unavailable data, it might be concluded that, in drier regions, it would be similar to that of *Ulmus* spp. Previous studies have proposed that, in water-limited environments, trees may be increasingly vulnerable to die-off in response to drought and heat stress (Allen et al., 2010; Adams et al., 2009). For example, in Inner Asia, further increases in environmental stress and tree mortality are potentially driving the eventual regional loss of current semi-arid forests due to warming (Liu et al., 2013). Facing climate changes, including drought, *Pinus edulis* in semi-arid woodlands near Los Alamos in USA were found to be dying off due to leaf-water potentials remaining near their zero-carbon assimilation point (Breshears et al., 2009).

Due to decreasing precipitation and rising temperature, desert areas in mid-latitude regions are expanding, and conditions in water-scarce regions will become drier (Lu et al., 2015). These changes would have detrimental effects on the tree species (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) in eastern deserts (Hulun Buir, Horqin, and Otindag). Therefore, ecological engineering using trees in these regions should be implemented cautiously, and flexible measures and policies should be considered to restore vegetation.

In addition, in this study, the VSI of vegetation dominated by *H. ammodendron* and *H. persicum* in the Gurbantunggut was relatively low (Fig. 4 and Table 5), which shows that tall shrubs in this locality were less sensitive to climatic variations. This exception to the above mentioned results is mainly related to local groundwater (Chen et al., 2008), and adequate snowmelt is also an important water source in this region (Fan et al., 2014). Hence, precipitation was not the main climatic factor affecting vegetation activities in this region, and, in the VSI calculation process, precipitation contributed less than temperature to changes in vegetation (Table 5).

### 4.3. Implications and limitations

We emphasise that the vegetation types had different vulnerabilities in water-limited environments. Compared with dwarf shrubs, the trees (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) and tall shrubs (*Caragana* spp.) were generally more vulnerable to climate variations. Under the projected climate change in northern China, the climate will continue to warm and drought stress will intensify. All these factors impact trees and tall shrubs more intensely than they do dwarf shrubs, and, in the worst-case scenario, this may result in the degradation of vegetation dominated by trees and tall shrubs. This implies that, in light of the climate change across the desert region of northern China, drought-tolerant plant species (e.g. dwarf shrubs) should be prioritised in ecological restoration projects. In terms of existing vegetation, areas dominated by trees and tall shrubs should be strictly protected to avoid further deterioration of vegetation caused by the negatively coupled effects of anthropogenic disturbances (e.g., grazing) and climate change. Rational ecological engineering and differentiated ecosystem

conservation could effectively maintain vegetation alongside sustainable development. Consequently, the 'Zero Net Land Degradation' goal for the desertified regions can be achieved more efficiently (Prăvălie et al., 2017).

Vegetation dynamics are generally driven by climate, particularly precipitation, solar radiation, air temperature, and atmospheric humidity (Ratzmann et al., 2016). To assess the relative sensitivity of global terrestrial ecosystems to climate, Seddon et al. (2016) used air temperature, water availability, and cloud cover as climatic factors affecting vegetation activities in the VSI equation. For desert ecosystems, temperature and precipitation were the main climatic factors (Yang et al., 2015; Sun et al., 2015), and we did not consider the effect of solar radiation in our VSI calculation process.

Our study quantified vegetation responses across two environmental conditions (temperature and precipitation) and allowed us to identify major climatic constraints on remotely sensed vegetation. However, the results could contain some discrepancies due to the unevenly distributed meteorological stations across different climate regions. For example, a few stations in the hyper-arid region could have resulted in uncertainties in the interpolation of climatic factors. Although the climate regions were classified based on the most recent AI data, our results could also have been influenced by collected AI data, the time frame of which (1981–2010) did not completely overlap with our study period (1982–2015). Thus, the combination of multi-resource spatial data (such as global aridity data) could improve the accuracy of the results (Prăvălie, 2016). In addition, we investigated the responses of vegetation to climatic factors using a vegetation index (NDVI), but the structure and function of vegetation and anthropogenic disturbances, such as grazing, should also be considered in future research. Finally, to calculate the VSI in desert ecosystems, the relationship between NDVI and climatic factors at different times should be further researched.

## 5. Conclusions

The responses of vegetation to climatic variations in the desert region of northern China were investigated, based on trend analysis and VSI. The results show that during the growing seasons of 1982–2015, there were distinct trends in vegetation across the study area. Vegetation dominated by *P. sylvestris* var. *mongolica*, *Ulmus* spp., and *Caragana* spp. were more sensitive to climatic variations than that dominated by *A. desertorum*, *A. ordosica*, *H. persicum*, and *H. ammodendron*. Our results demonstrate that vegetation responses to climatic variations varied across the study area: Vegetation dominated by trees (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) and tall shrubs (*Caragana* spp.) was more sensitive to climatic variations than that dominated by drought-tolerant dwarf shrubs (e.g., *A. desertorum* and *A. ordosica*). Our study suggests that distinct strategies for protecting vegetation should be considered and developed to combat land degradation in the desert region of northern China, and ecological engineering with trees (*P. sylvestris* var. *mongolica* and *Ulmus* spp.) and tall shrubs (*Caragana* spp.) in eastern deserts (Hulun Buir, Horqin and Otindag) should be implemented with caution. We also suggest that future studies need to focus on the impact of drought, the influence of anthropogenic disturbance, and the legacy effect of climatic factors in evaluating the VSI of desert ecosystems.

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